Analyzing the Connection between Social Isolation and Deaths of Despair in Ohio

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Abstract

This paper examines the potential connection between social isolation and deaths of despair in the state of Ohio using data from 2016. The emergence of an upward trend in deaths caused by suicide, alcohol-abuse, and drug overdoses presents the United States with a pervasive and cross-cutting problem that is believed to have caused the first decline in American life expectancy in decades. Over the past five years, Ohio, in particular, has been significantly impacted by the scourge of so-called 'deaths of despair.' At the same time, in an increasingly connected world, health behaviors have a more profound impact on individual, community, and population health than ever before; while technological and societal advances allow people to be more connected to one another than ever before, the traditional concept of community in the United States is less and less part of Americans' everyday lives. Social isolation, however, is an increasingly prominent adverse health behavior that is being observed throughout the world and is directly linked to negative health outcomes. The potential connection between the increase in social isolation and the emergence of the trend in deaths of despair informed the following questions: What is the relationship, if any, between social isolation and deaths of despair in Ohio's 88 counties? Are there differences in relationships between social isolation and specific types of deaths of despair in Ohio's 88 counties? Utilizing multivariate regression modeling, statistical analysis was performed on a dataset consisting of rates of mortality, social connectedness, and population characteristics for each of Ohio's 88 counties to evaluate the potential for a link between social isolation and deaths of despair. The results showed that while there is not a correlation between social connectedness and deaths of despair, counties with high comparative unemployment rates and populations of Ohioans over the age of sixty-five have higher rates of deaths of despair. Additionally, it was found that social isolation is significantly and positively correlated with the rate of drug overdoses per county. The absence of an explicit connection between social isolation and deaths of despair in this study, however, scrutinizes how social connectedness and social relationships are measured in empirical studies. In conclusion, it is recommended that future research on social isolation include both physical and digital measures of social connectedness and closely examine the relationship between social isolation and deaths of despair to conditions of aging and unemployment.

Key words and phrases: deaths of despair, social isolation, social connectedness, social determinants of health, socio-ecological model, health behaviors, population characteristics, individual and community health factors, Facebook friendships

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Introduction

Recent media coverage has focused on the so-called "Rust Belt" and, more specifically, on the state of Ohio as a victim of shifting population demographics, economic trends, and overall societal devastation in the United States. Droves of news stories have tried to explain why college-educated individuals flock away from the state after graduating (Milligan, 2019). Ohio's overall population is much older, on average, than most of the rest of the United States, and regions of the state still suffer greatly from the loss of steel manufacturing over the past 50 years. *Hillbilly Elegy*, J.D. Vance's New York Times best-selling memoir, is a perfect anecdotal example of the manifestation of these trends in the lives of many Ohioans: dealing with the reality of a loved one's addiction to drugs and alcohol, growing up in poverty, and navigating the educational system with little support at home. The culmination and collective interest in this topic has led social science researchers to study what exactly is occurring in states like Ohio – and the results are troubling. A new cultural phenomenon, dubbed 'deaths of despair,' has arisen, classified by these states experiencing a spike in deaths caused by suicide, alcohol abuse, and drug overdose.

The term 'deaths of despair,' popularized by Princeton professors Anne Case and Angus Deaton (2015) in their academic research refers primarily to the decreasing life expectancy of Americans due to rising rates of mortality by suicide, drug overdose, and alcohol-related illnesses. Life expectancy, commonly viewed as a reliable measure of overall population health for countries throughout the world, has risen steadily in most developed nations for the last century (Woolf and Schoomaker, 2019). A recent study, however found that the United States experienced a decline in life expectancy of white, middle-aged adults (particularly men) from 2010-2017 in certain regions, the magnitude of which has not been seen since World War I

(Woolf and Schoomaker, 2019). As a result, the concept of deaths of despair has caught the attention of various economists, policymakers, and public health researchers (Diez Roux, 2019). Much of the existing literature and research on this topic focuses on the factors driving each individual type of death of despair; suicide, drug overdose, and alcohol abuse-related mortality.

The nature and general public perception of deaths by suicide, drug overdose, and alcohol abuse also motivate recent academic interest on the phenomenon because of how these kinds of preventable deaths are socially perceived. Generally, there is a social stigma associated with the causes of death that comprise the deaths of despair phenomenon (Case and Deaton, 2020). Additionally, social connectedness and social isolation are two increasingly relevant topics in public health research attempting to explain the various factors that affect the health of individuals. Since these deaths have an inherent social component, it is worth examining the potential connection between social isolation and deaths of despair. Social connectedness can be defined as an objective measure of the number and frequency of an individual's social contacts, while social isolation is the lack thereof. Adverse health effects of social isolation have been likened and popularly equated to smoking 15 cigarettes per day in previous studies (Holt-Lunstad, 2015). For these reasons, social isolation is being explored as a possible factor influencing the increase of so-called 'deaths of despair' that the United States has experienced over the past decade (Case and Deaton, 2015).

It is also important to note that decades of policy efforts at the local, state, and federal-levels have continually failed to address the structural problems experienced by individuals living in states like Ohio, as noted above – widespread poverty, an extremely unstable and volatile job market, and increasingly worse health outcomes at a population-level (Guilford, 2017). Only in the past five years, driven primarily by an interest in the massive upheaval of the traditional American political landscape, has the plight of these “forgotten” individuals begun to be considered (MacGillis, 2016). Despite this desire to draw an explanation as to what is driving deaths of despair, there is little-to-no published academic work focusing on overall individual behaviors and underlying causes that affect this pressing cultural phenomenon. As a result, examining the possibility of a connection between social isolation and deaths of despair in Ohio, one of the regions most affected by the increase of deaths of despair, is warranted.

The following empirical analysis aims to quantify the effect of social isolation on deaths of despair. The empirical analysis focuses on the examination of deaths by suicide, drug overdoses, and alcohol-related health issues in Ohio’s 88 counties, relying on data from the Ohio Department of Health Public Data Warehouse and the American Community Survey. The trend of deaths of despair and its overarching effect on society in the United States, specifically communities across the state of Ohio, gives way for the following research questions to be posed:

1. What is the relationship, if any, between social isolation and deaths of despair in Ohio’s 88 counties?

2. Are there differences in relationships between social isolation and specific types of deaths of despair in Ohio’s 88 counties?

Literature Review

The following literature review examines the historical context of previous research on social isolation and loneliness, the three different 'types' of deaths of despair; suicide, drug overdoses, and alcohol-related mortality, social determinants of health, social isolation as a social determinant of health, and the relation of social isolation to economic well-being and employment opportunities. These areas of research explore how social isolation has been viewed historically as it relates to health outcomes, the three distinct causes of mortality that make up deaths of despair, and how employment opportunities and the state of the economy affect social isolation and subsequent health outcomes. The following review of extant research informs the application of a theoretical framework, the socio-ecological model for health promotion and prevention, to social isolation and deaths of despair.

First, it is important to look closely at the existing research on social isolation and loneliness and how individuals across disciplines have defined these concepts and related them to health behaviors and outcomes. Next, providing an overview of the social determinants of health is imperative to understanding social isolation as a determinant of health. Additionally, establishing the relationship in research between social networks, connectedness, and isolation is critical for any study on the effects of social isolation as a factor in individual health outcomes and as a driver in the emerging trend of deaths of despair, a cultural phenomenon. Analyzing literature surrounding the three specific classifications of deaths of despair is also appropriate for a study on the connection of social isolation to deaths of despair. Lastly, recognizing the effect that the state of the economy and the availability of employment opportunities have on social isolation and subsequent health outcomes is necessary, in addition to considering social isolation as a negative health behavior.

Evolution of Social Isolation Research

Existing literature on social isolation as a health behavior of concern has evolved considerably over the past five decades, initially examining the relation of these conditions to suicide and now, in a broader sense, taking an upstream approach to analyzing social isolation and health. The early study of social connectedness in a sociological perspective established that a lack of social elements in the life of an individual, or social isolation, acts principally as a driver of suicide. Moreover, social connections were understood as fundamental to the holistic – physical, biological, and psychological – health of individuals and cohesion of societies (Durkheim, 2002). To that point, work on the subject focused primarily on the established relation of social connections to mental and psychological health, yet these findings led researchers to believe social isolation played a significant role in individual health outcomes (House, Landis, and Umberson, 1988).

Individuals across disciplines then turned to quantitative examinations of social connectedness to learn more about the effect of social isolation on physical health. When comparing social isolation to other risk factors, one particular finding showed that individuals with a history of cardiac issues and a high degree of social connectedness experience better health outcomes after a heart attack than individuals who were not socially connected (Case et al., 1992). In this study, social connectedness was measured by whether or not consenting patients who experienced major cardiac events lived alone. More recently, meta-analytic research found that social isolation has a profound effect on and the overall health of individuals, with social connectedness proven as a significant risk factor for morbidity and mortality akin to cigarette smoking and potentially more impactful than commonly-known risk factors such as obesity and physical inactivity (Holt-Lunstad, Smith, and Bradley, 2010). The most significant quantitative measurement of social connections created thus far was completed by Rupashinga et al. (2006), who created a social capital index on the county-level from information based on the number of civic organizations in the area, voter participation rates, census response rates, and the number of non-profit organizations in the area. Recognizing how the study of social connectedness as a social determinant of health has developed over time, gradually and inconspicuously, is important in acknowledging how social connectedness relates to health promotion, prevention, and behaviors. The literature, however, suggests that social isolation has extensive effects on health, communities, and societies that necessitates further research.

Social Connectedness, Social Isolation, and the Social Determinants of Health

Any examination of factors affecting individual health and well-being warrants a discussion of the social determinants of health, or the conditions and resources that impact health including but not limited to economic stability, physical environment and neighborhood, education, nutrition, access to quality healthcare, and community or social elements such as social connectedness and support systems (Aly, 2018). Soon after the World Health Organization (WHO) established the Commission on Social Determinants of Health (CSDH), the body produced evidence declaring that widespread health inequities are the result of inadequate social programs, unethical economic conditions and policies, and a failure of political leaders and parties throughout the world (CSDH, 2008).

Social isolation, the quantifiable absence of social connectedness experienced by individuals, is implicitly recognized as a product of the inadequate social programs, unethical economic conditions and policies, and failures of world leadership in the lens of the social determinants of health. Furthermore, the Centers for Disease Control and Prevention (CDC) utilizes a model displaying the social determinants of health which illustrates psychosocial factors like social connectedness that affect intermediate outcomes such as health-promoting behaviors as well as the long-term outcomes of individual and community health (Ramirez, Baker, and Metzler, 2008). The identification of social connectedness as a determinant of health represents the acknowledgement of social isolation as a comprehensive cultural issue, affecting not only the health of individuals but also encompassing the well-being of communities.

The concept of modifiable factors that influence health, drawing from social determinants of health, numerically quantifies the degree to which four areas affect individual health: health behavior, social environment, physical environment, and economic environment (Booske et al., 2010). Modifiable factors that influence health are broken down accordingly; the health behaviors, like tobacco and alcohol use, that an individual engages in influence 30% of an individual's health, socioeconomic factors (like education, income, and social support and connectedness) influence 40% of an individual's health, the physical environment in which one lives influences 10%, and access to and quality of healthcare influences 20% of their overall health (ICSI, 2014). Social connectedness, therefore, should be classified a cross-cutting determinant of health that merits attention for health prevention because it is an aspect of the socioeconomic portion of modifiable health factors and is influenced by physical environment, impacts access to healthcare, and can predict health behaviors (Woolf and Aron, 2013). As such, social connectedness and social isolation permeate into other aspects of society.

The Relationship Between Health Inequity and Social Isolation

Assessing how health inequities impact health-promoting behaviors for individuals, as well as the specific mechanisms and results of an absence of social connectedness on individual and community health, is necessary for a study of social isolation and its designation as a force responsible for adverse health outcomes. Health equity is often defined as the state in which all individuals have the opportunity to achieve full health potential and no one is prevented from achieving their full health potential because of social position or circumstance (Baciu et al., 2017). Health inequities are often manifested through antiquated norms and systems of social standing, such as discrimination based on socioeconomic class, ethnic or religious group, race, or gender, leading only to further systematic discrimination of these disenfranchised individuals with particular effects on their health (Braveman and Gruskin, 2003). The effects of health inequity on an individual's ability to engage in healthy behaviors, disposition to favorable socioeconomic factors, residence in a safe physical environment, and access to quality healthcare warrant serious consideration in effectively and efficiently addressing health policy (Whitehead, 1992). The negative effects of health inequity described by Whitehead correlate almost exactly with the modifiable factors of health, further solidifying the connection between structural health equity, the social determinants of health, and health outcomes.

One of the most evident ramifications of social isolation's vast impact on health can be contextualized through marginalization, or the peripheralization of individuals according to their identities, associations, experiences, and environment (Hall et al., 1994). In the United States, individuals with drug addictions, alcohol dependency, and mental illness, in addition to refugees and immigrants, are often marginalized and thus socially isolated (Lynam and Cowley, 2007). Recent research also highlights that older adults from vulnerable, or marginalized, populations are at greater risk of social isolation and other health disparities later in life (Goldsen, 2019). Given this research, health inequity in the United States exacerbates the effects of the marginalization of these populations and demonstrates how harmful social isolation is for individual and community health (Baah, et al., 2019). This research leads to further examination of the realistic potential for social isolation, a negative consequence of inequities in the determinants of health, as what could be driving the increase of deaths of despair in the United States.

Social Isolation and Deaths of Despair in the Context of Health Behaviors

Understanding engagement in and maintenance of social connections as a health-related behavior provides a lens to view how social isolation, the lack of engaging and maintaining social connections, intersects with the trend of deaths of despair. Health-related behaviors are actions, intentional or unintentional, that affect individual health and mortality (Short and Mollborn, 2015). Social isolation or a general lack of social connections has not historically been viewed as a health behavior, while actions such as cigarette smoking and physical activity have been historically and continually pointed to as behaviors that affect health. Extensive research, however, has proven that social connectedness has health consequences that rival those of smoking 15 cigarettes per day and increases the risk of heart attacks (Brummett et al., 2001). Recognizing that deaths of despair can be attributed to damaging health behaviors stemming from social and economic factors in individual communities across the United States, particularly the rural and Appalachian regions experiencing the most intense increase of deaths of despair (Stein et al., 2017).

There is also strong evidence establishing a link between the adjustment of adverse health behaviors and mortality accounting for socioeconomic status (Stringhini et al., 2010). Classifying social isolation as a consequence of adverse health behaviors and acknowledging that social isolation has the potential to drive deaths of despair, a cultural phenomenon that permeates every cognitive, biological, emotional, and behavioral aspect of individual and community health and well-being in the United States, provides a viable approach to further understanding the trend of deaths of despair (Shanahan et al., 2019).

Educational Attainment, Employment Opportunities, the Economy, and Social Isolation

Considering what effect the state of the economy and availability of employment opportunities have on social connectedness is imperative when looking at the impact of social isolation in the United States from an overall societal perspective. First, it is important to acknowledge the role that educational attainment plays in impacting an individual's sense of social standing and social support, which lead to better health behaviors, increased familial stability, less stress, and greater economic resources, all resulting in improved overall individual health (Braveman, Egerter, and Williams, 2011). Putnam's (2016) *Our Kids* echoes this sentiment and takes a step farther, identifying the widening disparities in educational attainment as one of the driving factors for the continual increase in social isolation and the decline in overall social ties in the United States. Well-established research also illustrates that individuals who experience social isolation have fewer opportunities for mobility because they lack social ties that could get them ahead in the highly competitive American job market (Burt, 1997).

There is a lack of academic work that looks in-depth at the potential of declining employment opportunities in particular regions, paired with the changing nature of work and the types of jobs available in the United States, to perpetuate social isolation at both an individual and community-level. In this context, the impact of employment as a social determinant of health merits consideration; economic stability is often considered an overarching social determinant of health, with more specific factors being access to adequate education, employment, and the quality of job-training (CSDH, 2008). A growing body of literature on economic factors, however, explains that increasing income inequality, declining employment opportunities in the United States manufacturing sector, and the growth of technology such as automation have the potential to completely transform of the employment market in the United States (Autor and Dorn, 2013). This hypothesis can be linked to declining absolute income mobility, or the possibility for children to earn more than their parents when adjusted for economic differences over time, indicating the "American Dream in decline" (Chetty et al., 2016). A recent study explores the role of employment and economic well-being, quantifying that declining marriage rates in the United States can be attributed to the changing dynamic and make-up of the American economy (Autor, Dorn, and Hanson, 2019). These studies reflect the anecdotal evidence presented by J.D. Vance (2016) in *Hillbilly Elegy*, who describes the lack of high-quality, well-paying employment opportunities and subsequent social issues at length throughout his story of growing up in Middletown, Ohio during the 1990's.

Given that employment is a social determinant of health, a more in-depth examination of how an individual's employment status affects their health behaviors and health outcomes. First, it is important to acknowledge that among all of the impacts that employment has on the livelihood of individuals, work and employment status have an especially marked effect on individual health behaviors like the use of tobacco, overall mental health and well-being, and access to quality healthcare (Akah and Reat, 2018). In this case, unemployment, lower incomes, and the type of health insurance coverage offered by employers can directly and indirectly influence health behaviors and subsequent health outcomes. Another important, yet often over-looked, health behavior that is affected by unemployment is social connectedness. Fundamental literature on the relationship of unemployment to health finds four specific mechanisms connecting unemployment, ill health, and, mortality: the role of relative poverty, social isolation, health behaviors, and the effect of unemployment on future work opportunities (Bartley, 1994). In *Bowling Alone*, Robert Putnam presents a similar explanation of the relationship between unemployment and social connectedness: individuals facing unemployment become passive and socially withdrawn, relating to a rise in stress rises and a decline in civic engagement (2000). Other research about social participation and social capital suggests that unemployment drives rising income inequality in the United States, which in turn is related to health outcomes; people who were poor because of unemployment or low wages were found to have positive health outcomes if they were not deprived or restricted in any way from social participation (Marmot, 2002). Work itself is an inherently social endeavor however more specialized research illustrates a deep connection between unemployment, social isolation, and poor health behaviors and outcomes.

Deaths of Despair: Suicide, Drug Overdoses, and Alcohol-related Mortality

The scope of the health and societal effects of social isolation, the decline in life-expectancy experienced in recent years, and the shifting dynamic of the United States economy justify an analysis of deaths of despair in the United States that pays particular attention to the importance of social connections. As a social phenomenon, 'deaths of despair' reflects the recent increase in rates of morbidity and mortality of Americans, representing a reversal in the century-long increase of life expectancy in the United States (Schutchfield and Keck, 2017). Seminal research on deaths of despair points to a dramatic increase in midlife death by suicide, drug overdoses, and alcohol-related mortality as cause for the increase in death rates of middle-aged, white, American men without a college education (Case and Deaton, 2015).

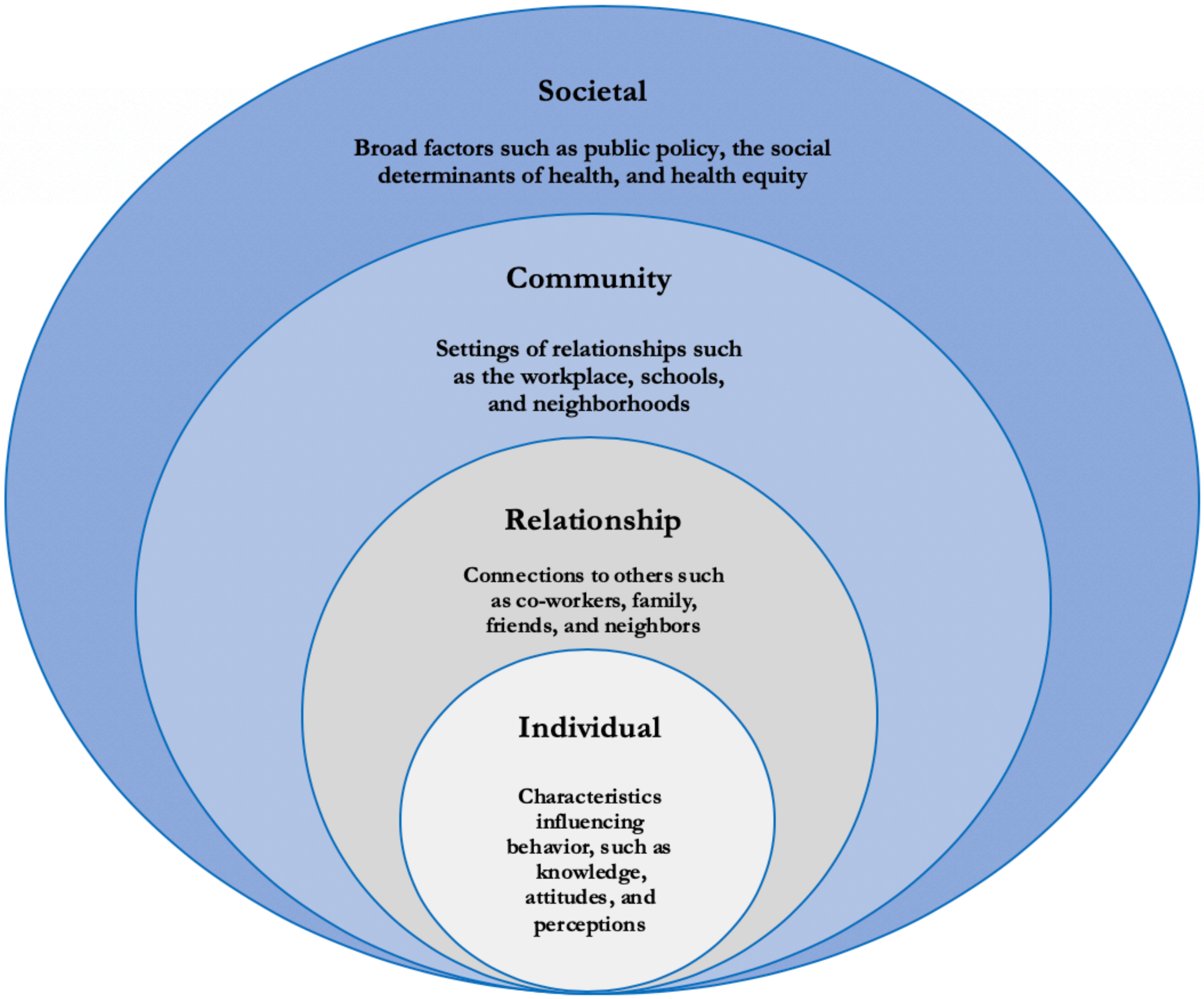
In recent years, the CDC began paying particular attention to deaths of despair in specific geographic areas throughout the United States, stating that the mortality increase in rural areas is significantly higher when compared with mortality rates in urban areas (Moy, Garcia, Bastian, et al., 2017). A body of empirical evidence reinforces these claims; one study focusing on deaths of despair found that rates of death by suicide, drug overdose, and alcohol-related diseases grew significantly over time leading up to 2015, where the rate of death by diseases of despair in Appalachian regions of Ohio, West Virginia, Kentucky, and Pennsylvania far outpaced the death rate by diseases of despair in non-Appalachian regions of the states (Meet, Heffernan, Tanenbaum, and Hoffman, 2017). The trend of deaths of despair has caught the attention of experts spanning disciplines, but the correct approach to the problem remains unseen (Diez Roux, 2017).

Despite decades of comprehensive literature and research specifically examining the deaths of despair phenomenon and deaths by suicide, alcohol abuse, and drug overdose, there is no extant study looking at the potential relationship of social connections and deaths of despair. Social media, given its growing prominence and use by individuals throughout the world (Chou et al., 2009), represents a possible method for quantitatively measuring the volume of social connections in certain areas, but not the quality of these digital connections. Recent data shows that Facebook is popular among all demographics of individuals in the United States, though younger individuals and more educated individuals are more likely to use the platform than others (Gramlich, 2019). Considering this information, the following study undertakes an exploratory examination of the potential connection between social isolation, as measured by the Social Connectedness Index built by researchers from Facebook data (Bailey et al., 2017), and deaths of despair in Ohio's 88 counties, measured by data from the Ohio Department of Health.

Conceptual Framework: The Socio Ecological Model as a Framework for Social Isolation

A socio-ecological model can illuminate the relationship between the varying factors that influence suicide, drug overdoses, and alcohol-related illnesses along with the adverse health consequences of social isolation. General ecological models in public health research emphasize the importance of focusing on individual, social, and environmental factors in prescribing solutions that address individual, relationship, community, and societal factors of health behaviors (McLeroy et al., 1988). The socio-ecological model of health behaviors and promotion is applicable to the analysis of the potential connection between social isolation and deaths of despair because it assumes that the social environment in which individuals live will lead to changes in health behaviors, and that individuals must embrace these changes for them to effect health outcomes (McLeroy et al., 1988). Figure 1 illustrates the functional application of the socio-ecological model to social isolation and social connectedness. Viewing social isolation through the lens of the socio-ecological model, which emphasizes the importance of changing the environment in which people live to influence subsequent behaviors and considers multiple levels of factors that impact health behaviors, is appropriate within the context and scope of the aforementioned research questions (Cohen, Scribner, and Farley, 2000).

Figure 1. Applying Social Connectedness and Social Isolation to the Socio-Ecological Model



Adapted from the Centers for Disease Control and Prevention 2020.

Skills, past experience, self-concept, knowledge, attitudes, and beliefs shape individual factors of the socio-ecological model for health behaviors and promotion, the first layer of factors in the model (Sallis et al., 2006). These individual factors are particularly influenced by personal characteristics, such as age, sex, race and ethnicity, and educational attainment (Golden and Earp, 2012). For social isolation, past experiences could include the loss of specific social contacts or connections because of death or physical distance, while attitudes could relate to self-sufficiency and individualism. The second layer of the socio-ecological model for health behaviors and promotion is relationship factors, representing the most pertinent link to social connectedness and social isolation. Relationship factors within the socio-ecological model are based on the different natures of relationships and social networks individuals have, such families, work groups, and friendships (McLeroy et al., 1988). It is necessary to also consider the volume of connections that individuals have when looking at the relationship layer of the socio-ecological model; this examination informs any kind of potential measurement of social connectedness or social isolation based on relationships.

Community factors, the third layer in the socio-ecological model, encompass the social and organizational characteristics of institutions and how they are both formally and informally connected through social networks (McLeroy et al., 1988). More importantly, the community layer of the socio-ecological model emphasizes the need to acknowledge the settings in which social relationships occur, building directly from the second layer of factors, which are based on social relationships. Further contextualizing the community layer of the socio-ecological model is important; for example, the labor market is an organizational factor of employment in a community, while the settings of social connections are structurally different in rural counties than in urban counties. The socio-ecological model frames societal considerations, such as the social determinants of health, public policy, and health equity as imperative in predicting health behavior and subsequent individual and community health outcomes. The socio-ecological model, however, presents the societal layer as the farthest away from individual factors, showing that procedurally and realistically, the nature of implementing changes based on these factors varies greatly (Sallis et al., 2006). While the societal layer is farthest away from the individual layer, the societal layer encompasses the community, relationship, and individual layers, illustrating that societal factors permeate all other factors included within the socio-ecological model for health behaviors and promotion. Furthermore, utilizing the socio-ecological model to critically examine the potential relationship between social isolation and the trend of deaths of despair is necessary because addressing societal, community, relationship, and individual factors requires systematic interventions that affect entire populations, as opposed to interventions that only affect individual participants or specific groups of people (Glanz and Mullis, 1988).

Research Questions

Returning to the original research questions, this section describes the statistical models and related hypotheses:

1. What is the relationship, if any, between social isolation and deaths of despair in Ohio's 88 counties?

2. Are there differences in relationships between social isolation and specific types of deaths of despair in Ohio's 88 counties?

This study undertakes an exploratory analysis of the potential relationship between deaths of despair and social isolation in Ohio's 88 counties in 2016. Based on previous empirical research, there is an implicit assumption that social isolation is related to the recent upward trend in deaths of despair throughout the state of Ohio's 88 counties (Holt-Lunstad et al., 2010).

Related literature on the subject also suggests that deaths of despair is a cultural phenomenon that disproportionately affects middle-aged white men without college degrees living in rural areas (Case and Deaton, 2015). As such, it was necessary to control for the following characteristics; age, race, gender, geographic location, and educational attainment of a bachelor's degree. Since no previous empirical analyses or literature have examined the potential relationship between deaths of despair and social connectedness, there are no implicit assumptions for an answer to the second research question.

Empirical Strategy

To test the effect of social isolation, the inverse of social connectedness, on the rate of deaths of despair in Ohio's 88 counties, multivariate regression analysis was performed using four different models. Model 1 is the base model, analyzing how significantly, if at all, the rate of deaths of despair in Ohio's 88 counties is impacted by the sum of Social Connectedness Index (SCI) scores per capita, a control variable for population density of each county, and a suite of population and socioeconomic characteristics, consisting of percentages of individuals in three age groups in the county, percentage of individuals by sex, percentage of individuals by the five most common racial/ethnic groups, a dummy variable for whether or not the county is rural or urban, the unemployment rate of each county, and percentage of individuals in each county earned a bachelor's degree. The base multivariate regression tests whether social connectedness (as measured by the SCI) affects the rate of deaths of despair in the state of Ohio, using a county-level analysis to address the first research question. The equation for the base regression model is as follows:

Base Multivariate Regression Model

$$\textbf{Model 1:}\ \text{Total Deaths of Despair} = \beta_0 + \beta_1 \mathit{SCI} + \beta_2 \mathit{PopulationDensity} + \beta_3 \mathit{age2} + \beta_4 \mathit{age3} + \beta_5 \mathit{Men} + \beta_6 \mathit{White} + \beta_7 \mathit{AmericanIndian} + \beta_8 \mathit{Asian} + \beta_9 \mathit{Hispanic} + \beta_{10} \mathit{Rural} + + \beta_{11} \mathit{UnemploymentRate} + \beta_{12} \mathit{CollegeGrads} + \varepsilon$$

The alternate regression models, Models 2, 3, and 4, include interaction terms meant to examine the effect of relationships between the variables for percentage of men and percentage of white individuals per county, the variables for percentage of men and percentage of "middle-aged" individuals per county, and the variables for percentage of men per county and percentage of rural counties overall. Models 2, 3, and 4, shown below, further test whether social connectedness measured by SCI score per capita affects the rate of deaths of despair through a county-level analysis of Ohio:

Alternate Regression Models (with interaction terms)

$$\textbf{Model 2:}\ \text{Total Deaths of Despair} = \beta_0 + \beta_1 \mathit{SCI} + \beta_2 \mathit{PopulationDensity} + \beta_3 \mathit{age2} + \beta_4 \mathit{age3} + \beta_5 \mathit{Men} + \beta_6 \mathit{White} + \beta_7 \mathit{AmericanIndian} + \beta_8 \mathit{Asian} + \beta_9 \mathit{Hispanic} + \beta_{10} \mathit{Rural} + \beta_{11} \mathit{UnemploymentRate} + \beta_{12} \mathit{CollegeGrads} + \beta_{13} \mathit{White*Men} + \varepsilon$$

$$\textbf{Model 3:}\ \text{Total Deaths of Despair} = \beta_0 + \beta_1 \mathit{SCI} + \beta_2 \mathit{PopulationDensity} + \beta_3 \mathit{age2} + \beta_4 \mathit{age3} + \beta_5 \mathit{Men} + \beta_6 \mathit{White} + \beta_7 \mathit{AmericanIndian} + \beta_8 \mathit{Asian} + \beta_9 \mathit{Hispanic} + \beta_{10} \mathit{Rural} + \beta_{11} \mathit{UnemploymentRate} + \beta_{12} \mathit{CollegeGrads} + \beta_{13} \mathit{Men*Age2} + \varepsilon$$

$$\textbf{Model 4:}\ \text{Total Deaths of Despair} = \beta_0 + \beta_1 \mathit{SCI} + \beta_2 \mathit{PopulationDensity} + \beta_3 \mathit{age2} + \beta_4 \mathit{age3} + \beta_5 \mathit{Men} + \beta_6 \mathit{White} + \beta_7 \mathit{AmericanIndian} + \beta_8 \mathit{Asian} + \beta_9 \mathit{Hispanic} + \beta_{10} \mathit{Rural} + \beta_{11} \mathit{UnemploymentRate} + \beta_{12} \mathit{CollegeGrads} + \beta_{13} \mathit{Men*Rural} + \varepsilon$$

The alternate regression models differ from the base model because these models have interaction terms, which are meant to examine whether the interaction of particular variables indicates a significant effect of an explanatory variable on the dependent variable at different values of other explanatory variables. The choice of which variables to interact with one another is derived from the widely held belief that deaths of despair in the state of Ohio disproportionately affect white, middle-aged men living in rural areas. As a result, variables examining the interaction between the variable for percentage of white individuals and percentage of men per county, the interaction between the variable for percentage of middle-aged individuals (ages 35-64) and percentage of men per county, and the dummy variable for rural counties and percentage of men per county were constructed.

Answering the second research question requires a test of whether social isolation significantly affects one of the causes of deaths of despair, suicide, alcohol-abuse, or drug overdoses more than others in Ohio's 88 counties; as such, further multivariate regression analyses was performed. In the three additional iterations of the analysis, however, the rates of death by suicide, alcohol abuse, and drug overdoses per 1,000 people in each county were used as the dependent variables. Model 5 will use the rate of deaths by suicide per 1,000 people in each county to analyze how significantly, if at all, the rate of deaths by suicide in Ohio's 88 counties is impacted by the sum of Social Connectedness Index (SCI) scores per capita, percentage of individuals residing in each county in three separate age groups, percentage of men and women per county, percentage of individuals residing in each county that fall into the five most common racial/ethnic groups, a dummy variable for whether or not the county is rural or urban, the unemployment rate of each county, and percentage of individuals in each county who received a bachelor's degree. Model 6 used the rate of deaths by alcohol abuse per 1,000 people per county while Model 7 used the rate of deaths by drug overdose per 1,000 people per county to examine the potential connection between these death rates and the same explanatory variables used in Model 5, described above. Models 5, 6, and 7, designed to answer the second research question, are shown below:

Additional Regression Models (with different regressands):

Model 5: Total Deaths by Suicide = $\beta_0 + \beta_1 \mathit{SCI} + \beta_2 \mathit{PopulationDensity} + \beta_3 \mathit{age2} + \beta_4 \mathit{age3} + \beta_5 \mathit{Men} + \beta_6 \mathit{White} + \beta_7 \mathit{AmericanIndian} + \beta_8 \mathit{Asian} + \beta_9 \mathit{Hispanic} + \beta_{10} \mathit{Rural} + \beta_{11} \mathit{UnemploymentRate} + \beta_{12} \mathit{CollegeGrads} + \varepsilon$

Model 6: Total Deaths by Alcohol Abuse = $\beta_0 + \beta_1 \mathit{SCI} + \beta_2 \mathit{PopulationDensity} + \beta_3 \mathit{age2} + \beta_4 \mathit{age3} + \beta_5 \mathit{Men} + \beta_6 \mathit{White} + \beta_7 \mathit{AmericanIndian} + \beta_8 \mathit{Asian} + \beta_9 \mathit{Hispanic} + \beta_{10} \mathit{Rural} + \beta_{11} \mathit{UnemploymentRate} + \beta_{12} \mathit{CollegeGrads} + \varepsilon$

Model 7: Total Deaths by Drug Overdose = $\beta_0 + \beta_1 \mathit{SCI} + \beta_2 \mathit{PopulationDensity} + \beta_3 \mathit{age2} + \beta_4 \mathit{age3} + \beta_5 \mathit{Men} + \beta_6 \mathit{White} + \beta_7 \mathit{AmericanIndian} + \beta_8 \mathit{Asian} + \beta_9 \mathit{Hispanic} + \beta_{10} \mathit{Rural} + \beta_{11} \mathit{UnemploymentRate} + \beta_{12} \mathit{CollegeGrads} + \varepsilon$

Testing the potential for a significant difference in how social isolation affects each of the three causes of deaths of despair – suicide, alcohol-abuse, and drug overdose – required each to be used as the regressand, or dependent variable, in the three iterations of the base multivariate regression model described and shown above. Before the regressions were computed, general database error-checking was performed by examining the correlations between variables, calculating the variation inflation factor (VIF) for the variables (Figure 2), and graphing the probability density of the model (Figure 3). Graphical representations of the results of the database error-checking can be found in the Appendix. Correlations between variables worth nothing include that between the variables for black and unemployment rate to the variable for deaths of despair, SCI score and population density to drug overdoses, white and black to SCI score, and rural county classification to population density. The calculation of the VIF showed normal variance between independent variables, and the probability density graph for the residuals was mostly linear.

Description of Data

To analyze what factors most significantly influence the rise of deaths of despair for Ohioans, a dataset was constructed from three separate sources: the Social Connectedness Index (SCI), the Ohio Department of Health Public Data Warehouse (ODHPW), and the American Community Survey (ACS) published by the United States Census Bureau. The Social Connectedness Index (SCI) is a first-of-its-kind quantitative measurement of social connectedness utilizing social media; the researchers who created the SCI gathered and anonymized information from Facebook users' friendship links between one another, specifically using United States county-pairs.

The independent variable of interest, aggregate SCI score per 1,000 people in each Ohio county, comes from a dataset constructed by a team of economists at Facebook, Harvard, Princeton, and New York University (Badger and Bui, 2018). Using an anonymized aggregation of Facebook friendships in April 2016, the SCI maps Facebook users to their presumed county of residence based on the regular IP address attached to the account. Only Facebook accounts that have shown activity from the user in the 30 days prior to the data extraction are included in the SCI, and each friendship is given equal weight, or value, in the data. From there, totals were calculated from the normalized total number of Facebook friendships between individual accounts for each county-to-county geographic pair, and as well as within each individual county itself. The SCI has a maximum value of 1,000,000, assigned to Los Angeles County-Los Angeles

County Facebook friendships, with relative differences in SCI values corresponding to relative differences in the sum of Facebook friendships. Facebook friendships are a good proxy of social connectedness because 71% of the United States online population used the platform as of 2014, the formation of a friendship takes the consent of the individuals controlling both accounts, and previous research illustrates that individuals tend to only establish links on Facebook to people they actually know (Duggan et al, 2015).

The Ohio Department of Health Public Data Warehouse (ODHPW) is an online self-service program allowing anyone to access available public health data about the state of Ohio from a variety of sources. This project used the ODHPW's Mortality dataset, which consists of the rates and counts of deaths among residents of Ohio from 2007 to present and is updated on a daily basis. Information on mortality published by the Ohio Department of Health comes from Ohio Certificates of Death, which reflect deaths of Ohioans regardless if they occurred within or outside of the state. Causes of death are part of the dataset, which adheres to the data collection, processing specification, and analysis methods outlined by the National Center for Health Statistics (Ohio Department of Health, 2020). The American Community Survey (ACS), published by the United States Census Bureau, is one of the foremost data sources for community characteristics and statistics used by American social science researchers. Data from the ACS is comprised of numerical breakdowns of various aspects of the American population, ranging from educational attainment, to breakdowns of areas by sex, race, and age. Results are collected annually for many areas, but more comprehensive datasets are published for 5-year periods of time (United States Census Bureau, 2020).

Answering the proposed research questions required the construction of the described dataset drawing from three sources because a, specific dataset measuring social connections, deaths of despair, while including population characteristics does not exist. Population characteristics must be considered here because of the application of the social determinants of health and structural inequity to deaths of despair drawn in this study; the characteristics of certain groups of individuals, as well as the resources and conditions they are disposed to, affect their overall health and well-being. Additionally, applying the socio-ecological model as a framework for the impact that social connectedness has on health warranted the use of population measurements and statistics in the study, given the focus of the model on individual, social, and environmental factors on prescribing cross-cutting policy solutions to complex problems.

In building the cross-sectional dataset, all data come from calendar year 2016, one of the years identified as having a particularly high volume of deaths of despair that contribute to a declining life expectancy for Americans. This study analyzed Ohio, which is continually identified as one of the hardest-hit states by the climbing trend of deaths of despair for its citizens. The unit of analysis is individual Ohio counties; because there are 88 counties in the state of Ohio, there are 88 observations in the dataset. To define and delineate the classification between rural and urban counties for the state, this study used the Centers for Disease Control (CDC) 2013 National Center for Health Statistics (NCHS) Classification Scheme for Counties (United States Department of Health and Human Services, 2017). The NCHS Classification Scheme for Counties was chosen for two reasons; (1) because this study is rooted in public health and health policy, and (2) because county was already chosen as the unit of measurement or analysis. For individual communities, counties, and cities to address structural health inequities that contribute to social isolation and ultimately deaths of despair, leaders in these areas must balance the needs of their population with the severity of the problem it faces.

The dependent variable was the total number of deaths of despair by county per 1,000 residents (Table 1). This variable was calculated by adding the total of deaths caused by suicide, alcohol-abuse, and drug overdoses in each county in 2016. General causes of death are coded and defined by the Centers for Disease Control National Vital Statistics System, and the Ohio Department of Health Public Data Warehouse guides researchers to use this classification of 39 different causes of death for the analysis of smaller geographic areas (National Center for Health Statistics, 2018). In the manual, categories X60-X84 consist of causes of death specified generally as suicide, categories Y10-Y19 consist of causes of death by poisoning after exposure to drugs, and categories beginning with K70 consist of causes of death from intentionally and unintentionally self-inflicted poisoning as a direct result of alcohol abuse. The rate of deaths of despair per Ohio county is population adjusted per-capita to standardize calculations between counties with varying populations and totals of deaths of despair.

The independent variables were total Social Connectedness Index (SCI) score per capita, percentage of individuals residing in each county in three separate age groups, percentage of men and women per county, percentage of individuals residing in each county that fall into the five most common racial/ethnic groups, a dummy variable for whether or not the county is rural or urban, the unemployment rate of each county, and percentage of individuals in each county who earned a bachelor's degree (Table 1). SCI score per capita was calculated by adding the total of the SCI scores for the county's Facebook friendships between all individuals within the county and of all individuals to people in other counties in the United States and dividing this sum by the population of each county in 2016. Below, Table 1 provides a list of the variables in the analysis, their measurement, and their source. Table 2 shows the descriptive statistics for the dependent variables used, and Table 3 shows the descriptive statistics for the independent variables used in the regression models.

Table 1: Variables, Measurements, and Sources

Variable	Measurement	Source
Suicide	Number of deaths in Ohio caused by suicide in 2016	Ohio Department of Health Public Data Warehouse
Alcohol Abuse	Number of deaths in Ohio caused by alcohol-use in 2016	Ohio Department of Health Public Data Warehouse
Drug Overdoses	Number of deaths in Ohio caused by suicide in 2016	Ohio Department of Health Public Data Warehouse
Deaths of Despair	Sum of deaths in Ohio due to suicide, alcohol-use and drug overdoses in 2016, adjusted per 1,000 county residents	Ohio Department of Health Public Data Warehouse
SCI per Capita	Sum of SCI score per county, adjusted per capita	Social Connectedness Index
Population Density	Total population of the county divided by land area in square miles	American Community Survey 5-Year Estimate (2012-2016)
Age	Percentage of individuals in each of the three age groups per county	American Community Survey 5-Year Estimate (2012-2016)
Sex	Percentage of individuals by sex per county	American Community Survey 5-Year Estimate (2012-2016)
Race/Ethnicity	Percentage of individuals by race per county	American Community Survey 5-Year Estimate (2012-2016)
Rural/Urban	Is the county rural? yes=1, no(urban)=0	American Community Survey 5-Year Estimate (2012-2016)
Unemployment Rate	Percentage of individuals unemployed per county	American Community Survey 5-Year Estimate (2012-2016)
Percentage with Bachelor's Degree	Percentage of individuals with at least a Bachelor's Degree	American Community Survey 5-Year Estimate (2012-2016)

Table 2: Descriptive Statistics (Dependent Variables)

Variable	Obs	Mean	Std.Dev.	Min	Max
Deaths of Despair	88	.509	.165	.183	.897
Suicide	88	.199	.045	.089	.369
Alcohol Abuse	88	.434	.034	.355	.576
Drug Overdoses	88	.400	.020	.311	.433

Table 3: Descriptive Statistics (Independent Variables)

Variable	Obs.	Mean	Std. Dev.	Min	Max
SCI per Capita	88	.199	.045	.089	.369
Population Density	88	292.392	472.182	31.69	2753.063
Age Group 2 (Ages 35 - 64)	88	.400	.020	.311	.433
Age Group 2 (Ages 65+)	88	.166	.023	.109	.235
Men	88	.497	.016	.476	.611
Women	88	.503	.016	.389	.524
White	88	.921	.070	.632	.986
Black	88	.041	.057	.002	.297
American Indian	88	.002	.001	0	.005
Asian	88	.003	.005	0	.030
Hispanic	88	.025	.021	.002	.095
Rural	88	.455	.501	0	1
Unemp Rate	88	.070	.019	.027	.112
% with Bachelor's Degree	88	.193	.082	.077	.525

Results

Interpretation of the output from the computation of multivariate regression analysis on the base model, Model 1, suggests a positive, statistically significant relationship between the percentage of individuals in the middle-aged and sixty-five and older age groups. These results confirm existing literature that show the rate of deaths of despair per county increases with greater populations of individuals older than thirty-five years old. The coefficient on the variable of interest, SCI per capita, is neither statistically significant nor has an impactful effect size. Additionally, the coefficient on the variable for SCI per capita has a positive coefficient, but based on literature and existing research on overall health effects of social isolation, one would expect this coefficient to be negative, meaning that as the level of measurable social connections rise, the rate of deaths of despair per county would fall. Relating back to the first research question, while this analysis does not suggest that higher SCI scores correlate to fewer deaths of despair per county, the results support the notion that certain aspects of the socio-ecological model, which are affected by individual characteristics such as age, lead to counties in Ohio experiencing a higher rate of deaths of despair.

Model 2, the alternate regression model including an interaction term for white men, shows statistical significance for the coefficients on the variables for the groupings for middle-aged and older Ohioans per county, the variable for percentage of men per county, the variable for percentage of white individuals for county, the variable for unemployment rate per county, and the interaction term between for white men itself. Similar to Model 1, the coefficient on the variable for SCI score per capita is not statistically significant and has an extremely small and unsubstantial effect size, despite its positive correlation to deaths of despair. The coefficients on both age group variables again suggest that the percentage of individuals ages thirty-five and older is positively correlated with rates of deaths of despair in Ohio counties. Additionally, both the variables for percentage of men and white individuals on the rate of deaths of despair per county are statistically significant and have a substantial effect size. Because of the inclusion of an interaction term for white men, the effect size of a larger share of men per county on the rate of deaths of despair in that county changes based on the percentage of white individuals in the county being analyzed; the variables for men and whiteness have more of a differential impact on the model due to the inclusion of the interaction term for white men. The variable for unemployment rate is also statistically significant, has a substantial effect size, and is positive, all of which are expected results based on the literature and prior research. Overall, the inclusion of the interaction term for white men shows that as the percentage of white men per county falls, rate of deaths of despair increases; another finding contrary to the novel operationalization of social connectedness presented in the study.

Model 3, the alternate regression model including an interaction term for percentage of individuals in the older age group and unemployment rate per county, shows again that the coefficient on the variable for SCI score per capita is not significant and has an extremely small and unsubstantial effect size despite its positive correlation to the rate of deaths of despair per county, running contrary to the stated hypothesis. The coefficient on the percentage of individuals in the older age group means that a higher percentage of these individuals per county leads to a significantly higher rate of deaths of despair. These results echo those of Model 1, in which a higher unemployment rate per county led to a statistically significant, higher rate of deaths of despair per 1,000 individuals. Interestingly, neither the interaction term nor the two variables it was constructed from are statistically significant, suggesting that the variables for men and the middle-aged group and the interaction term itself have no real effect on deaths of despair per county in Ohio.

Model 4, the alternate regression model including an interaction term for the percentage of men in rural counties, shows statistical significance for the variable for SCI score per capita but an extremely small and thus unsubstantial effect size on the rate of deaths of despair per Ohio county. Both age group variables also show statistical significance in this model, suggesting that the interaction term has an effect on how much a rise in the percentage of individuals above age thirty-five per county drives an increase in the rate of deaths of despair. In this model, the unemployment rate per county still has a statistically significant, positive coefficient and a substantial impact on deaths of despair, suggesting that as the unemployment rate increases in Ohio counties, so does the rate of deaths of despair per 1,000 people. All of these variables are impacted by the interaction term for men living in rural counties, but neither the interaction term nor the variables it is made from have statistical significance.

The results produced by Model 5 only show that the variable for the percentage of individuals ages sixty-five and older is statistically significant, suggesting that as the percentage of individuals in the age group of the oldest Ohioans increases per county, the rate of death by suicide also rises. Table 5 displays the results of Models 5, 6, and 7 and breaks out the dependent variable, deaths of despair, into three different categories: deaths caused by suicide, deaths caused by alcohol abuse, and deaths caused by drug overdose. Model 6, which uses the same explanatory variables but substitutes the rate of death by suicide with the rate of death by alcohol-abuse, shows results similar to those of Model 5 for the variable for percentage of individuals ages sixty-five and older. In Model 6, there is a statistically significant, positive correlation between the percentage of individuals above age sixty-five per county and the rate of death by alcohol-abuse, but the effect size on rate of death by alcohol abuse is less than that of Model 5. Additionally, in Model 6, the percentage of men per county has a statistically significant effect on rate of deaths by alcohol abuse.

While the design of Model 7 follows that of Models 5 and 6 by using rate of deaths by drug overdose per Ohio county as the regressand, the results of Model 7 differ from those of Models 5 and 6. First, the statistically significant positive coefficient on SCI per capita implies that as scores on the SCI increase, so does the rate of deaths by drug overdose in Ohio counties. As identified in earlier iterations of Models 1-4, however, the effect size of the coefficient on SCI score is so small that it realistically has no meaningful impact on the rate of deaths by drug overdose for Ohioans. Moreover, the variables for percentage of middle-aged individuals suggest that counties with larger shares of individuals in this age groups will see higher rates of death by drug overdose. The results are shown in Table 5 below and warrant further discussion in the findings section of this paper.

Table 4: Regression Results, Overall Deaths of Despair

VARIABLES	**Model (1)** Overall Deaths of Despair	**Model (2)** Overall Deaths of Despair	**Model (3)** Overall Deaths of Despair	**Model (4)** Overall Deaths of Despair
SCI per Capita	0.000817	0.000551	0.000776	**0.000909***
	(0.000518)	(0.000513)	(0.000524)	(0.000517)
Population Density	1.30e-05	0.000117	1.91e-05	-6.59e-06
	(8.06e-05)	(8.88e-05)	(8.14e-05)	(8.10e-05)
Age Group #2 (35-64 years old)	**1.737***	**1.557***	-17.05	**2.025****
	(0.885)	(0.860)	(28.77)	(0.900)
Age Group #3 (65+ years old)	**2.254****	**2.053****	**2.512****	**1.775***
	(0.893)	(0.868)	(0.980)	(0.943)
Men	-0.136	**80.81****	-15.01	0.787
	(1.012)	(33.19)	(22.79)	(1.182)
White	-0.523	**44.38****	-0.637	-0.109
	(1.853)	(18.49)	(1.869)	(1.860)
American Indian	19.96	21.73	20.38	21.14
	(14.15)	(13.72)	(14.22)	(14.06)
Asian	3.451	3.212	3.136	4.187
	(3.316)	(3.212)	(3.364)	(3.327)
Hispanic/Latinx	-0.438	-0.204	-0.471	-0.302
	(0.961)	(0.935)	(0.966)	(0.957)
Rural	0.0591	0.0466	0.0605	1.738
	(0.0375)	(0.0367)	(0.0377)	(1.135)
Unemployment Rate	**2.053***	**2.335****	**2.049***	**1.947***
	(1.096)	(1.067)	(1.100)	(1.089)
% with a Bachelor's Degree	-0.000286	-0.0610	0.0253	-0.0450
	(0.330)	(0.321)	(0.334)	(0.329)
White Men		**-88.70****		
		(36.35)		
Men in Age Group #2			37.36	
			(57.18)	
Men in Rural Counties				-3.373
				(2.278)
Constant	-0.377	**-41.29****	7.174	-1.280
	(2.056)	(16.89)	(11.74)	(2.129)
Observations	88	88	88	88
R-squared	0.470	0.510	0.473	0.486

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 5: Regression Results, Individual Causes of Deaths of Despair

VARIABLES	**Model (5)** **Deaths by Suicide**	**Model (6)** **Deaths by Alcohol Abuse**	**Model (7)** **Deaths by Drug Overdose**
SCI per Capita	4.55e-05	-6.12e-05	**0.000833***
	(0.0002)	(0.0002)	(0.0005)
Population Density	-1.16e-05	-2.59e-06	2.67e-05
	(2.77e-05)	(2.17e-05)	(7.07e-05)
Age Group #2	0.125	-0.0141	**1.628***
(35-64 years old)	(0.326)	(0.256)	(0.833)
Age Group #3	**0.815*****	**0.594****	0.837
(65+ years old)	(0.295)	(0.231)	(0.753)
Men	0.0157	**0.495***	-0.643
	(0.371)	(0.291)	(0.947)
White	-0.0606	-0.153	-0.277
	(0.219)	(0.172)	(0.559)
American Indian	0.568	-2.289	21.67
	(5.234)	(4.108)	(13.36)
Asian	-0.0847	0.413	3.131
	(1.218)	(0.956)	(3.108)
Hispanic/Latinx	-0.295	-0.156	0.0242
	(0.282)	(0.221)	(0.719)
Rural	0.000355	0.00568	0.0529
	(0.014)	(0.011)	(0.035)
Unemployment Rate	0.542	0.361	1.151
	(0.403)	(0.317)	(1.030)
% with a Bachelor's	0.0366	0.0938	-0.128
Degree	(0.0011)	(0.008)	(0.0027)
Constant	-0.0266	-0.143	-0.242
	(0.371)	(0.291)	(0.948)
Observations	88	88	88
R-squared	0.211	0.230	0.384

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Discussion of Findings

Decades of well-established public health literature establish how social isolation is driven by structural health inequities, other social determinants of health, and overall individual health behaviors. This wealth of academic work related to social connectedness demonstrates a clear link between social isolation and adverse health outcomes. These negative health outcomes range from short-term illnesses, to chronic diseases, and even to mortality in extreme cases as a direct, traceable result of social isolation. Holt-Lunstad, Smith, and Layton (2010) found through their groundbreaking meta-analysis on social relationships and mortality that when comparing socially isolated individuals with socially connected individuals, individuals experiencing social isolation are at a 29% higher risk of death. Focusing on the mitigation of social isolation is extremely valuable in efforts to improve individual and community health outcomes.

Despite the clear theoretical connection of social isolation to causes of mortality, no comprehensive study has been conducted to date using an explicit, numerical measurement of the volume of social connectedness per area by proxy of social media to explain the trend of deaths of despair. Other proxies, ranging from the average number of confidants by generation, the occupancy of households, and the rate of marriage, have been used as measures for social isolation (Konrath, 2019). Until recently, researchers have largely relied on sociological and economic principles, theories, and trends to attempt to explain what could be causing the sizable increase of deaths of despair in the United States. The state of the economy and demography certainly play a significant role in the rise of deaths of despair, yet the pervasive and wide-ranging effects of social isolation as a social determinant of health and product of structural health inequities in the United States has yet to be analyzed utilizing quantitative means for an evaluation of the effects of social connections. A wide gap in existing literature on the subject was the primary motivation for this study and the use of the Social Connectedness Index (SCI) as the primary variable of interest in trying to explain the trend of deaths of despair in Ohio. Utilizing the SCI provides a unique opportunity to perform an analysis that aims to link the quantifiable measurement of social connections by geographic areas to cross-cutting and complex societal problems that are deeply rooted in public and community health, like social isolation and the emergence of the trend of deaths of despair. While the results of surveys and observations of national social trends provide valuable insight into the mechanisms and institutions through and in which social connections are declining, they fail to hold much power in explaining any local- or state-level trends in social isolation and related mortality. The SCI allows for just that: an opportunity to map social connections by geographic reasons and further utilize this mapping to explain specific trends within desired regions.

This quantitative study employed a county-level unit of measurement with the 88 counties in the state of Ohio. Restricting the empirical analysis to one state preserved a degree of cultural similarity across counties, although Ohio has a diverse population make-up with strong urban, suburban, and rural representation across the state. The use of counties within a single state also allowed for a degree of standardization among state-level policy and common public health practices, though specific local policies can vary greatly, especially between rural and urban areas (Pickvance, 2005). As shown through the analysis, individual characteristics of each county have varying relationships to the rate of overall deaths of despair and the rates of its individual causes of death – suicide, alcohol abuse, and drug overdose – in Ohio. The results of the different iterations of multivariate regression analyses presented in this study are both surprising and expected. Models 1-4, the base and alternative multivariate regressions aimed at answering the first research question, show that social isolation, as measured by the SCI, does not significantly impact the deaths of despair phenomenon in the state of Ohio. Furthermore, outputs of the regression analyses performed utilizing Models 1-4 (Table 4) point universally to the percentage of individuals over the age of sixty-five per county and the unemployment rate as common, significant correlates of deaths of despair in Ohio.

In attempting to answer the second research question, Models 5-7 (Table 5) show results suggesting again that the percentage of individuals per county in Ohio over the age of sixty-five is the primary factor driving the increase of deaths by suicide and alcohol-abuse, as this variable was found to be statistically significant in Models 5 and 6. Model 7 demonstrated that the rate of deaths by drug overdose in Ohio is heavily influenced by the percentage of middle-aged individuals per county and is higher in counties with higher rates of unemployment. In testing how social isolation is related to negative health outcomes through the analysis of the deaths of despair trend at the county-level, the findings of seven multivariate regression analyses showed no conclusive evidence that low scores on the Social Connectedness Index (SCI) are correlated with the rate of deaths by suicide, alcohol-abuse, and drug overdose within Ohio in 2016. The results of this quantitative study, however, strongly suggest that the percentage of individuals sixty-five and older per county, as well as the unemployment rate per county, hold explanatory power in examining deaths of despair in Ohio. The rate of unemployment per county is correlated to the rate of deaths of despair per county, which aligns with previous literature connecting unemployment rates and low incomes to poor health behaviors and outcomes, one of which is social isolation. When working to mitigate the impact of deaths of despair on the state of Ohio, the state should look towards policies specifically targeted at unemployed individuals.

The lack of a relationship between the Social Connectedness Index (SCI) and deaths of despair in the results of this study raises questions about the use of the SCI to measure social connectedness in examining deaths of despair, health behaviors, and population characteristics. An index constructed drawing purely from the user activity data of one social media platform, Facebook, is inherently unable to accurately measure all social connections within the United States. This study, however, represents an important first step in research efforts on the quantitative measurement of social connectedness and its potential relationships to health behaviors and subsequent health outcomes, such as deaths of despair. The userbase of Facebook represents the general American populous relatively accurately, referenced earlier, though certain groups are less likely to use this social networking site (Bailey et al., 2017). One group that is less likely to use Facebook is elderly Americans, a variable in the study identified as having a statistically significant impact on the rate of deaths of despair in Ohio. Additionally, individuals in specific geographic areas within Ohio could have been left out of the SCI measurement completely because of a lack of access to or adequate means by which to utilize high-speed broadband internet connections. Prior research on the topic suggests that there are considerable geographic disparities in ability to access high-speed broadband internet, as well as a degree of unwillingness to adapt to the new technology it inevitably brings (Strover et al., 2014).

As referenced earlier, any prescribed measurement of social connectedness has unique implications for the results of the research. Previous research has relied on qualitative methods of measuring social ties such as asking participants if they live alone, how many civic organizations an individual belongs to, or tracking how often they vote. The primary motivation behind using the SCI was to quantify a specific number of individual relationships and aggregate them by county, or a question that might be easier asked as; how many social connections do individuals in each county have? Any assignment of a particular measurement to social capital, connectedness, and isolation has implications that affects the results of the study. Moreover, this study examined the quantity, rather than any aspects of quality, of social connections measured by county-to-county (and intra-county) Facebook friendships.

Intuitively and practically, there is an inherent difference between connections that exist on a virtual platform as opposed to those that are physical and face-to-face by nature – Putnam strongly represented this school of thought, writing about the importance of face-to-face connections for building social capital in both *Bowling Alone* (2000) and *Our Kids* (2015). In most cases, Facebook friendships reflect 'real-life' social connections; Duggan et al. (2015) found that only 39% of individuals said that they have a Facebook friendship with another individual whom they have never met. The vast majority of Facebook friendships consist of close and distant family members, co-workers, former classmates, and other acquaintances. There is certainly a question to be asked about whether the effects of physical connections and are different than digital ones, and if these differences affect health and mortality by deaths of despair in different ways. The operationalization of social isolation only looking at quantity of social connections on social media affects the results of the study and necessitates future research looking at both quantity and quality of social connectedness for an examination of the relationship between social isolation and health outcomes.

This study also does not specifically address some other factors that literature might point to as having significant effects on deaths of despair and social isolation. First and foremost, because of the focus of the literature review on white, middle-aged men living in rural Ohio counties, there is little-to-no mention about elderly individuals. Since the variable for the percentage of individuals above the age of sixty-five per county was proven significant through all of the regression analyses, it is necessary to understand how recent gerontological research has shifted to examine how social isolation and loneliness affects seniors in the United States.

Recent scholarly research identifies that in a study of elderly subjects, 43% of participants felt lonely and experienced observable health issues as a direct result of their loneliness, leading the authors to conclude that loneliness was a predictor of functional decline and mortality (Perissinotto, Stijacic, and Covinsky, 2012). Seniors who are socially isolated and/or lonely are said to be twice as likely to develop Alzheimer's disease, at a comparatively high risk of premature cognitive decline, and far more likely overall to engage in unhealthy behaviors (AARP, 2018). Ohio has one of the most rapidly-aging populations in the United States, with the 2020 Census projected to show that there are more Ohioans over the age of 60 than there are Ohioans under the age of 20 – a rare trend compared to other states (Exner, 2019). There is a question, then, to be asked about condition of aging in the state of Ohio – are there any unusual factors driving worse outcomes for Ohio's aging population? This possibility represents an area ripe for future research on elderly Ohioans, their health outcomes, and deaths of despair.

Considering how social isolation and loneliness pervasively affects the health of seniors in the United States, the sustained correlation between the percentage of individuals over the age of sixty-five per county in Ohio and the rate of deaths of despair (in aggregate and individually), a more in-depth study into specifically what is driving deaths of people ages sixty-five and older is needed. There was also no mention of chronic disease, mental health considerations, or veteran status in the study. Each of these three characteristics are theorized to have some sort of role in affecting deaths of despair but were not included for analysis because of the scope of the study and for the purpose of brevity. Lastly, it is important to consider the possibility that deaths of despair are actually much higher than reported, due to what is printed onto the Ohio Certificates of Death. A large volume of anecdotal evidence, as well as a six-month study that took place in Vermont, suggests that errors on death certificates are more widespread than currently reported and accounted for (McGivern et al., 2017). This highlights a clear discrepancy in state and national data that prevents any measure of deaths of despair from being fully accurate.

Conclusion

Social isolation, the absence or lack of social connectedness, presents a growing threat to public health. As a social determinant of health and a product of structural inequity, social isolation negatively affects the health behaviors and overall health outcomes of individuals who have few social connections. The emergence of social isolation as a prominent and pressing public health issue warrants an examination of how individuals are currently affected by this phenomenon. Deaths of despair, or deaths by suicide, alcohol-abuse, and drug overdose, represent a pervasive and cross-cutting problem for the state of Ohio, which experiences comparatively high rates of these types of deaths. Because of the nature of these deaths and the established detriments that social isolation poses to an individual's health, an analytical study of the potential connection between social isolation and deaths of despair in Ohio was undertaken.

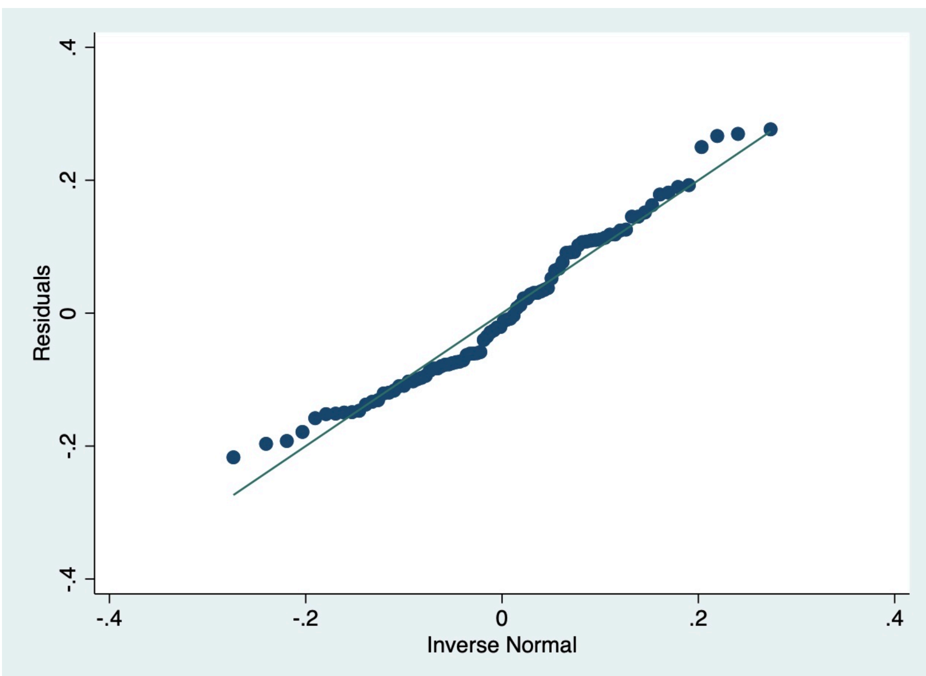
While literature suggests that social isolation adversely affects the health and well-being of all individuals, no previously existing research investigated the trend of deaths of despair using the lens or consideration of quantitative measurements of social isolation using social media as a proxy. The findings presented in this study, however, demonstrate that social connectedness (as measured by the Social Connectedness Index) has no significant effect on deaths of despair in the state of Ohio. Instead, the findings show that Ohio counties with a higher elderly population and Ohio counties with high relative unemployment rates are more likely to experience high rates of deaths of despair. These results suggest a possible shift from the framing of deaths of despair as a problem specific to white, middle-aged men to a problem prevalent among white, middle-aged men but also significantly influenced by the age distribution of populations and the employment outlook in certain areas. The regression results further suggested that the rate of Ohio deaths by drug overdoses might be influenced by different factors than the rate of Ohio deaths by suicide and alcohol-abuse.

Future research might explore different ways to code a variable representing social isolation or social connectedness that is more explicitly reflective of the population being studied, as the literature still suggests that social connections have a profound impact on individual health. As referenced throughout, how researchers choose to code any variable measuring social connectedness and social isolation is extremely important for the results of any study. Researchers should consider the explanatory power of pairing the SCI with another measure of the quality of social connections, such as surveys asking individuals why they use Facebook or if they consider the use of Facebook to be as fulfilling or gratifying as face-to-face relationships. Another avenue for further research involves potentially comparing the SCI to the number of civic organizations per county or its voter participation rate, as has been done in previous studies. Additional examination of the trends of deaths of despair might include the populations of other states experiencing this trend, such as Kentucky and West Virginia, or a time series panel of deaths over multiple years to see if this a significant trend. Finally, given the strong indication from the regression results that elderly Americans are most significantly driving deaths of despair, a more exact focus on this population may warrant in any future work on the subject. Overall, it is clear from the results of the study that in Ohio counties, the phenomenon of deaths of despair is connected to elderly and unemployed Ohioans, which should motivate future research on the subject.

Figure 2: Variance Inflation Factor (VIF) Chart

	VIF	1/VIF
White	8.725	0.115
Population Density	6.416	0.156
% with Bachelor's Degree	2.932	0.341
SCI per Capita	2.800	0.357
Unemployment Rate	2.170	0.461
Rural or Urban	1.771	0.565
Age Group #3 (65+ years old)	1.659	0.603
Age Group #2 (35-64 years old)	1.535	0.651
Hispanic	1.374	0.728
Men	1.355	0.738
Asian	1.253	0.798
American Indian	1.222	0.818
Mean VIF	2.768	0.277

Figure 3: Quantile Function of the Normal Probability Distribution Residuals



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